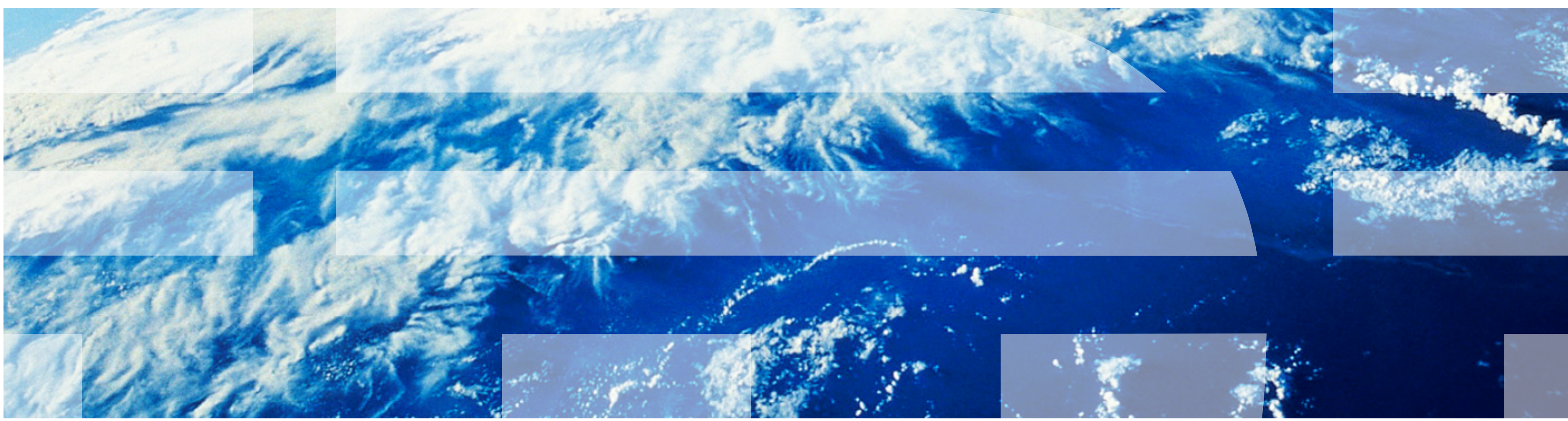
# Computer Systems for Data Science
# Topic 4

**Memory/Storage Hierarchy**

**Database and Key-value Store Architecture**



# What we'll cover

- **Memory and storage hierarchy and trade offs**
  - **DRAM**
  - **Flash**
  - **Disk**
  - **NVM**
- **Indexing**
- **Bloom filters**
- **Key-value stores**
  - **RocksDB**
- **Database on top of key-value store**
  - **MyRocks**

# Tasks of the database

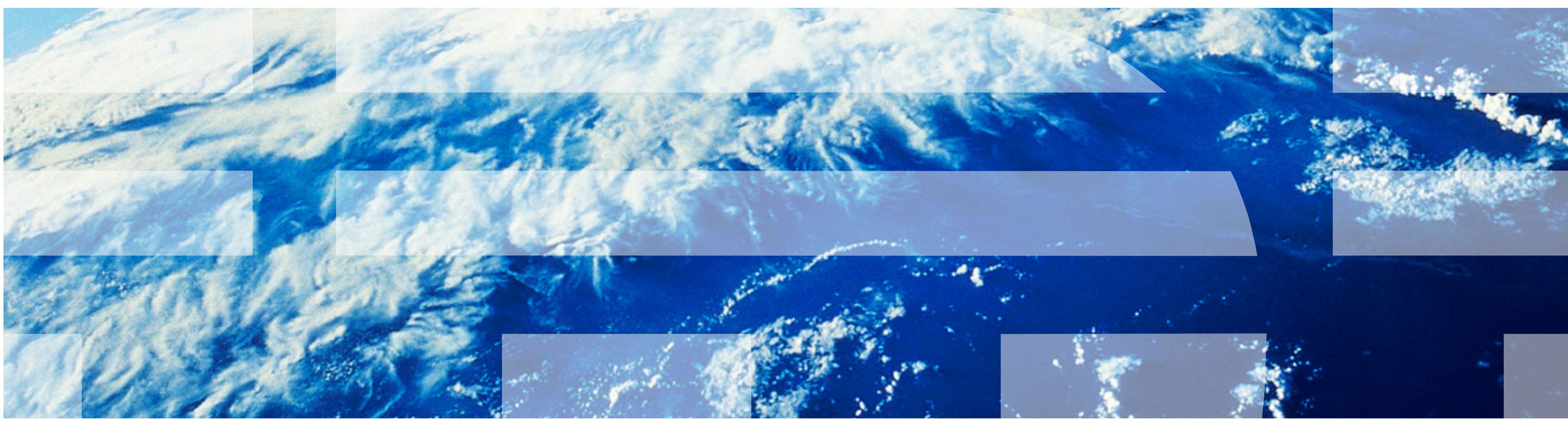
- Low level tasks:
  - Store the tables
    - Example: How do I physically store the tables on disk?
  - Read/insert/delete/update data
    - Example: What is the entry of cuid 1212?
- Higher level semantics:
  - Logging
  - Concurrency control
    - Example: what's the best schedule to execute a set of transactions?
  - Query optimization
    - Example: should I first do the projection, or the aggregation?

# We’ll focus on the systems aspects of some of these questions

- Low level tasks:
  - **Store the tables**
    - Example: How do I physically store the tables on disk?
  - **Read/insert/delete/update data**
    - Example: What is the entry of cuid 1212?
- Higher level semantics:
  - **Logging**
  - Concurrency control
    - Example: what’s the best schedule to execute a set of transactions?
  - Query optimization
    - Example: should I first do the projection, or the aggregation?

Borrowed/adapted from Greg Ganger

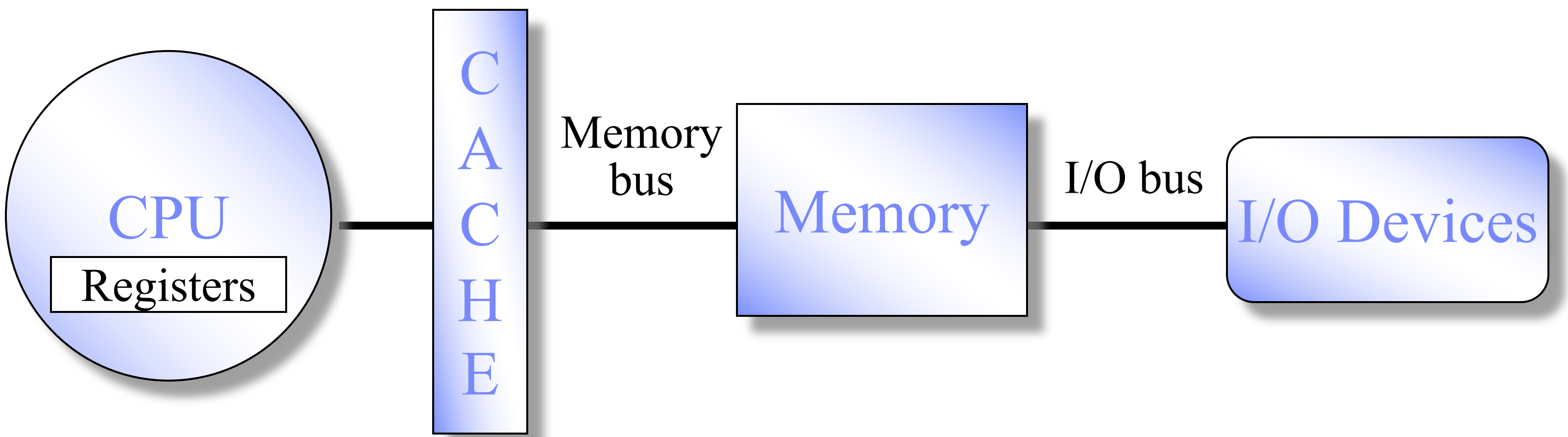
# Memory and Storage Hierarchy



# The memory hierarchy

- Memory and storage present several trade-offs:
  - Cost
  - Latency and throughput
  - Durability/volatility (is information lost when power goes down?)
  - Access granularity
- Can't have it all!

# The memory hierarchy



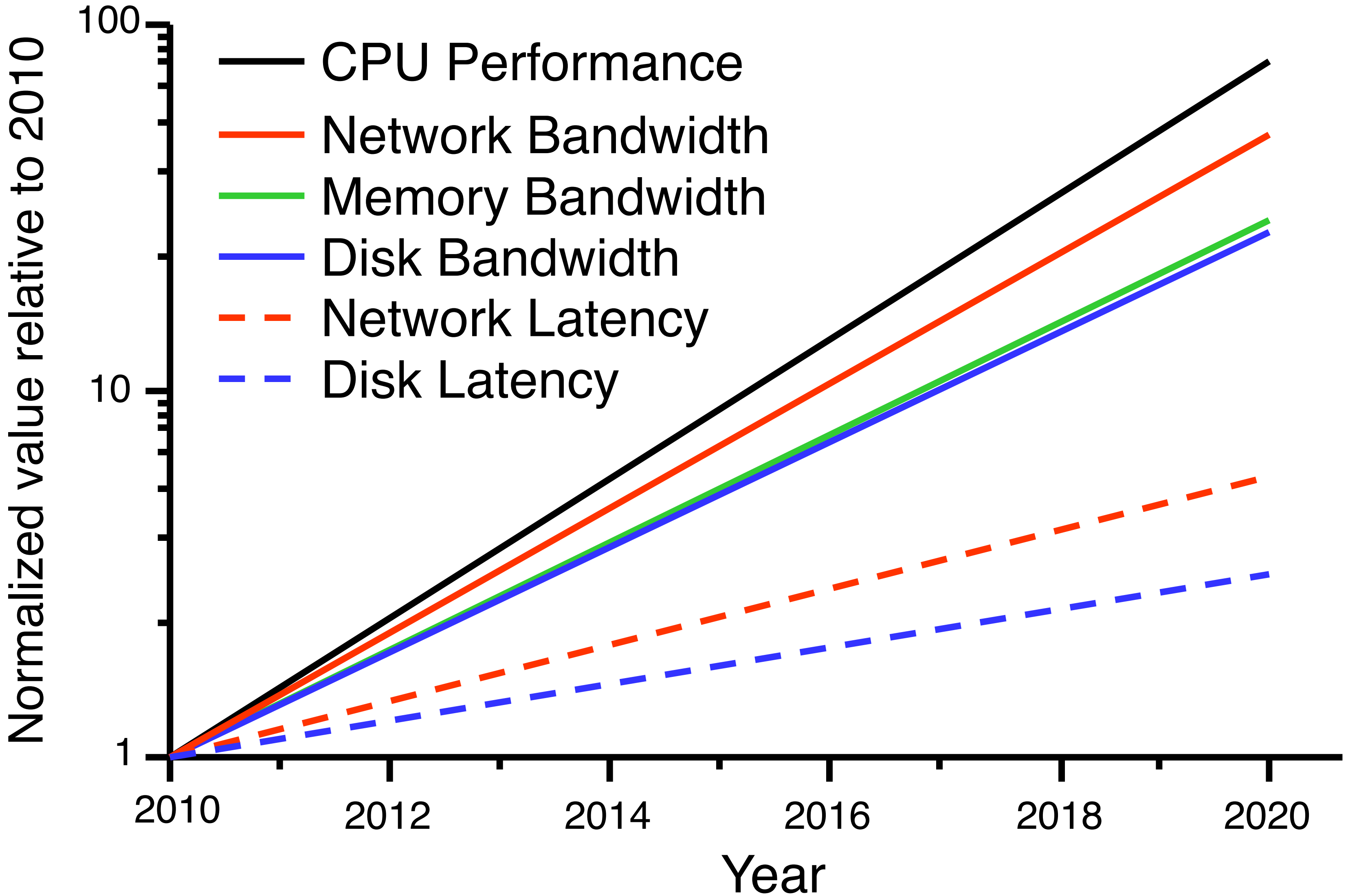

| | Register Reference | L1/L2/L3 Cache Reference | Memory Reference | Disk Reference |
|---|---|---|---|---|
| Size: | 300 B | 20 / 1 / 4 MB | 8-128 GB | 1-3 TB |
| Speed: | 0.2 ns | 1 / 5 ns | 25-100 ns | 5-10 ms (smaller, faster for Flash SSD) |

# Trade-offs (rough numbers)

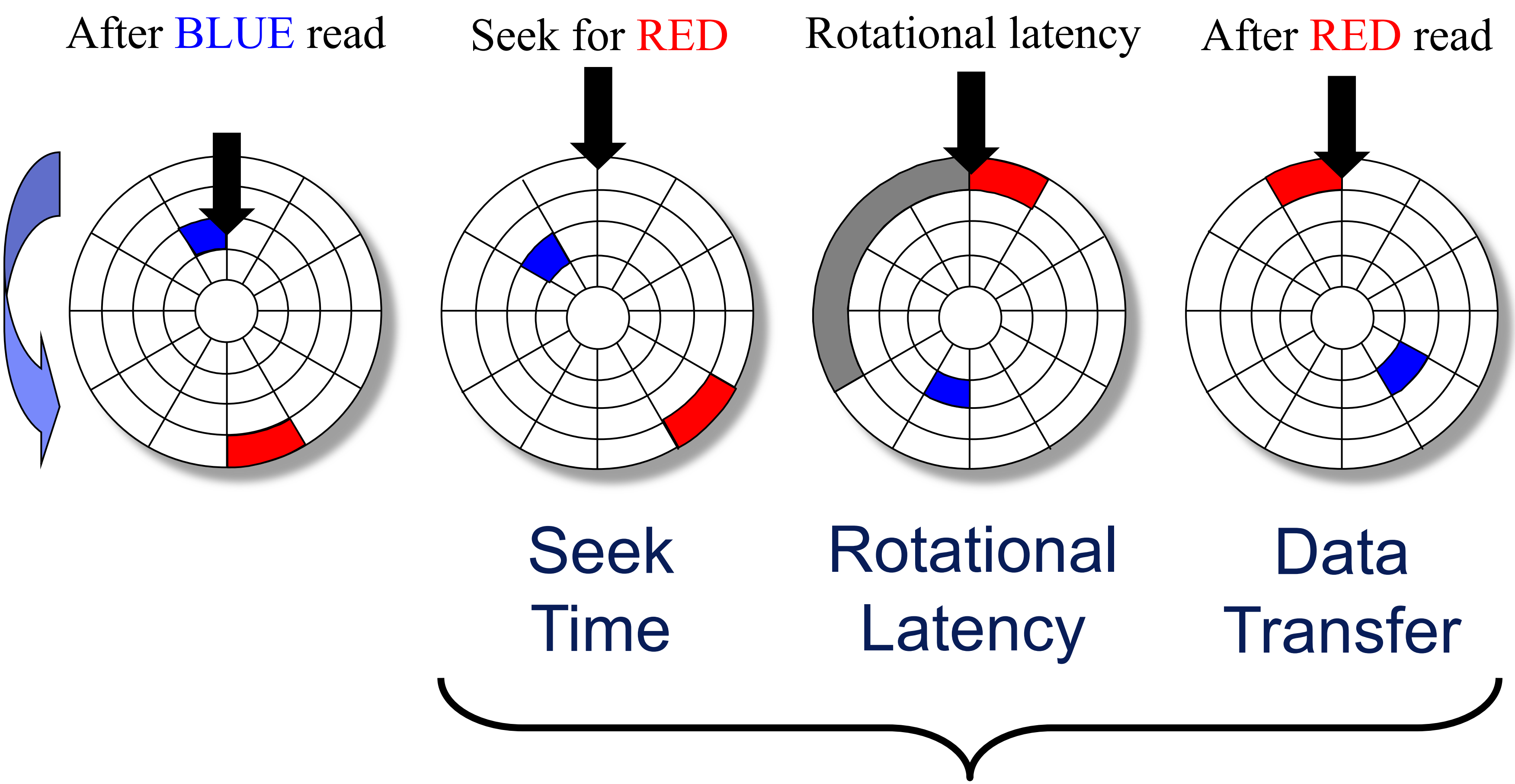
| | Memory (RAM) | Flash | Magnetic Disk |
|---|---|---|---|
| Cost/GB | $3 | $0.1 | $0.04 |
| Latency, random read | 25-100ns | 50-100us (1000X RAM) | 5-10ms (100X Flash) |
| Bandwidth, sequential reads | 10GB/s | 250MB/s | 150MB/s |
| Durable? | No | Yes | Yes |
| Effective access granularity | Byte reads and writes | 4KB read<br>MBs write | MBs read and write |

Sources:
https://jcmit.net/memoryprice.htm,
https://www.amazon.com/Intel-660p-1-0TB-80mm-978350/dp/B07GCL6BR4
https://www.amazon.com/Seagate-Portable-External-Hard-Drive/dp/B07CRG7BBH/ref=sr_1_3?keywords=hard+disk+1tb&qid=1579102708&sr=8-3

# Technology Trends



# HDD / Magnetic Disk

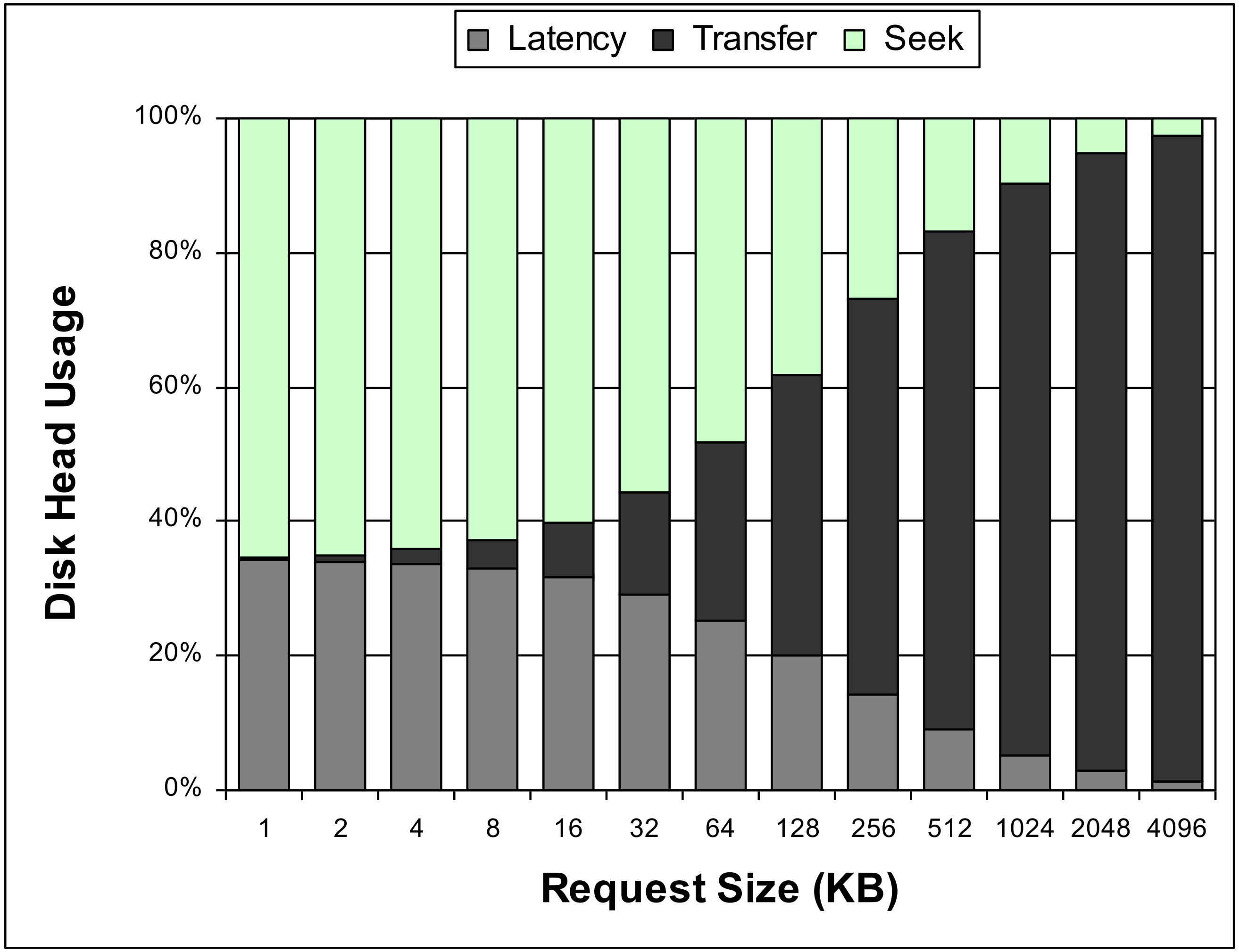



Access Time = seek time + rotation time
+ data transfer time
(for RED)

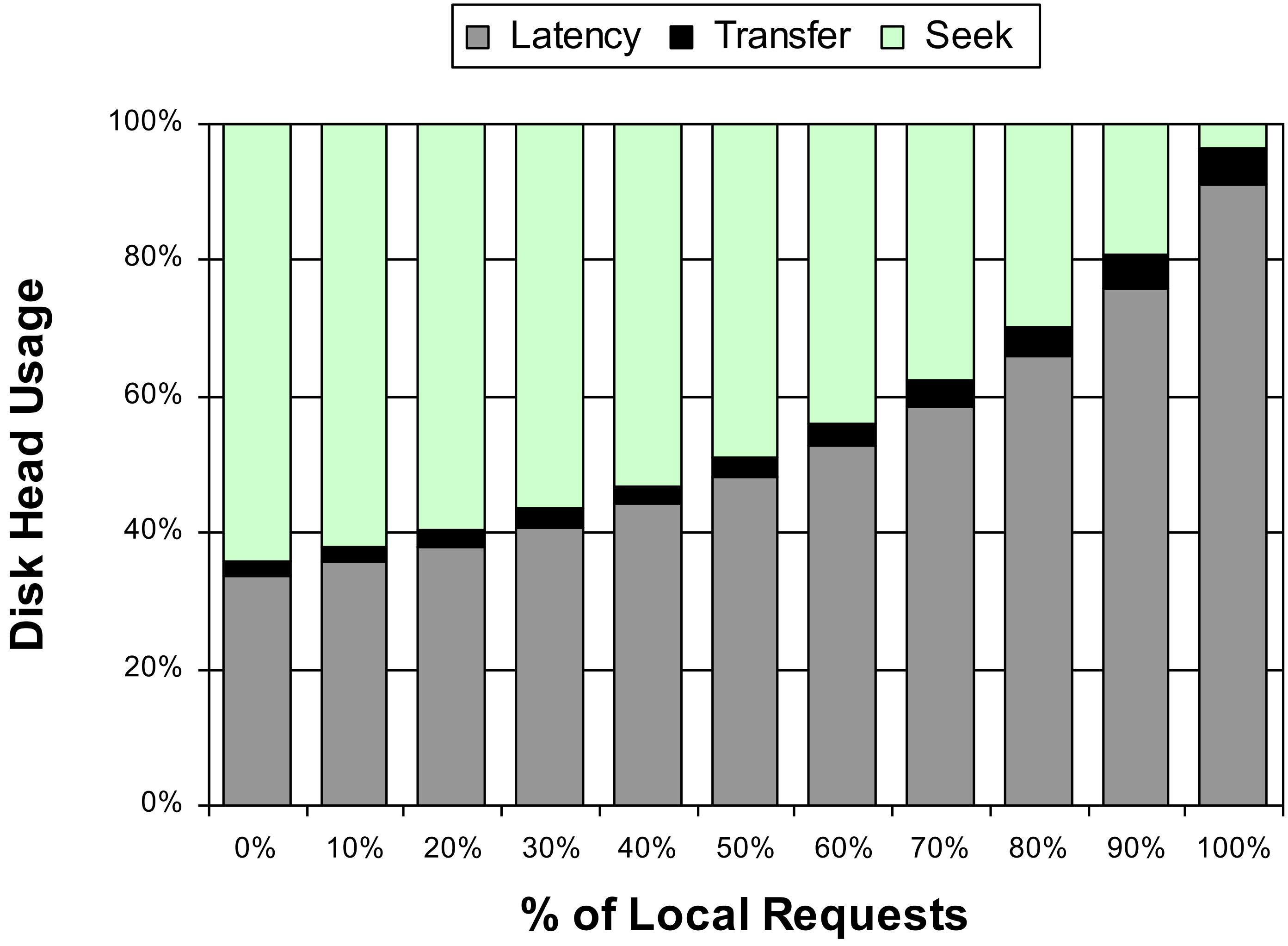
# Modern HDD performance

- Seek times: 1 – 6 ms, depending on distance
  - Average 2 – 4 ms
  - Not necessarily improving
    - It's a mechanical part!
- Rotation speeds: 4,200 – 15,000 RPM
  - Average latency of 2-12 ms
  - Typically slowing down
    - But also mechanical
- Data rates: 60-125 MB/s*, depending on zone
  - avg sector transfer time of 25 us
  - improving at 0-20+% per year

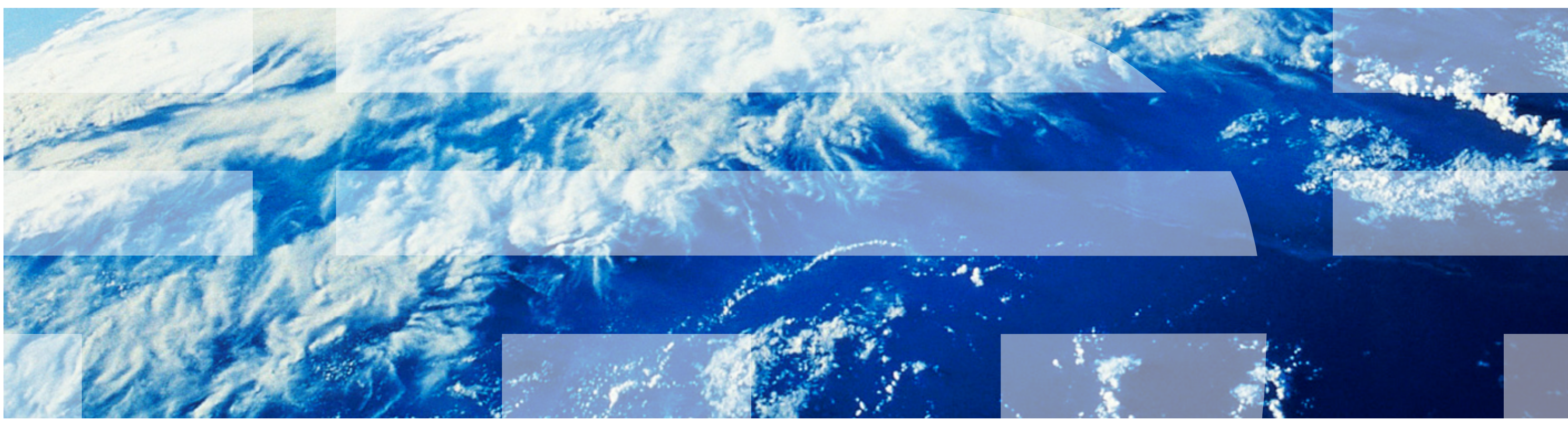
# HDD utilization (random requests)



# Locality is important (4KB requests)



# Lecture 6



# Recap of lecture 5

- **Conflicts and anomalies**
  - A conflict isn't necessarily bad – but we need to deal with it to avoid anomalies
  - Conflict serializable schedules are equivalent to serial schedules
  - Conflict serializability ←→ acyclic conflict graph

- **2PL**
  - How do we achieve conflict serializability in practice? 2PL is a family of algorithms that **guarantee** conflict serializability
  - Basic idea: Get S lock before read, get X lock before write, release locks only after acquiring locks
  - When do we acquire locks?
    - Strict 2PL: acquire as needed
    - Conservative 2PL: only acquire if all locks are available
  - 2PL needs to deal with deadlocks
    - Need to detect deadlocks with strict 2PL using waiting for graph
    - Conservative 2PL prevents deadlocks

# Recap of lecture 5 (continued)

- **Memory and storage hierarchy**
  - General trade off of cost vs. performance vs. durability
  - Difference technologies have different access granularities, which impact performance

- **Disk**
  - A disk access requires: seek + rotation + reading the data
  - Each of these has their own latency
  - Data locality crucially important for performance → sequential accesses have much higher performance

# Today: Indices, Bloom filters, KV stores and real DB example

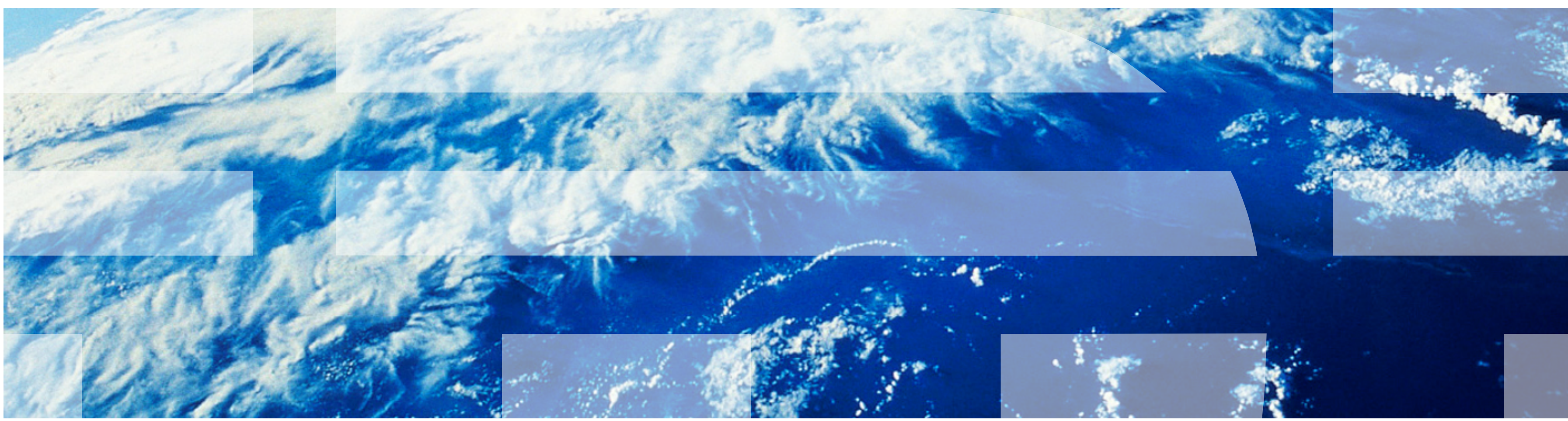
- Flash storage
  - Properties
  - Performance
  - Durability
- Different indexing schemes
  - Dense
  - Sparse
  - Secondary
  - Multilevel
- Bloom filters
  - Motivation
  - How they work
  - False positive vs. cache hit rate trade off
- Key-value stores
  - Spotlight on RocksDB
- Databases on top of key-value store
  - Spotlight on MyRocks

## Logistics

- Midterm on Monday
  - 2 hours: 4:10 – 6:10 PM, please be on time
  - You are allowed a cheat sheet: 2 two-sided letter pages
  - Besides cheat sheet, closed book, closed laptop

- Written homework due on Wednesday noon
  - Worth 10% of the grade

# Flash



# Flash

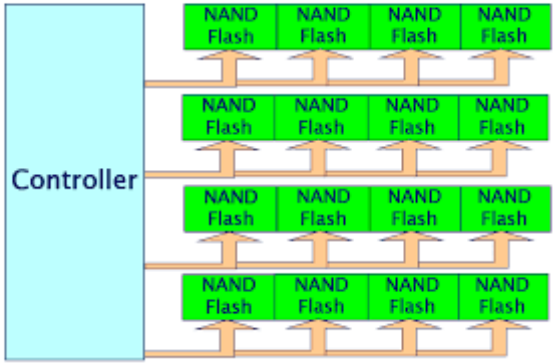
- Solid-state storage technology
  - Non-volatile memory chips, disk interface, **no mechanical moving parts (yay!)**
  - Fast access (no seeks) but more costly than mechanical disks
  - Lower power (~none if not accessing), noise free (laptops!)
- Performance differences
  - No seeks means high rates of small random access
- Reliability differences
  - Device fatigue (eventually stops being programmable)
  - Device retention (information leaks away)

# Flash performance is very different than magnetic disk

- Small random reads (no moving parts)
  - much, much lower average latency than mechanical disks
    - e.g., 10s of microseconds
  - orders of magnitude higher throughput than mechanical disks
    - e.g., 10s to 100s of 1000s of operations per second
- Write performance is more complicated
  - Small writes usually 100s of microseconds
    - Need to erase and reprogram flash cells → much longer time than reads
  - Write throughput more lower than reads for small objects
  - Need to write in large contiguous chunks (tens-hundreds of MBs) to get good performance

# Flash prefers large sequential writes

- Large sequential writes perform better on flash. Why?
- **Reason 1:** Erase granularity != write granularity
  - In order to write new data to flash, data needs to be erased first
  - Erasures are done in a block granularity:
    - Block is 4-16KB
  - Writing even 1 bit requires rewriting 4-16KB!
- **Reason 2:** Flash uses multiple channels to get high throughput
  - Writes are *multiplexed* across multiple chips in parallel for high throughput
  - A single logical written block gets chopped up into many physical blocks



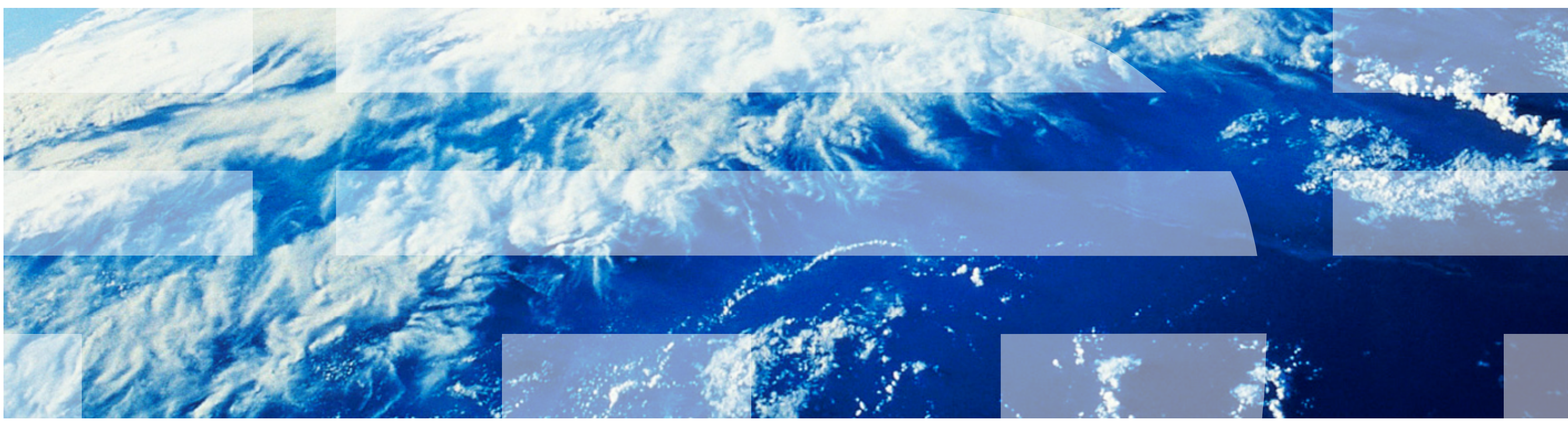

For optimal performance: writes typically need to be > 8MB!

## Wear leveling: spread writing evenly in SSD

- Each flash cell can only survive a given number of writes
  - 500 (USB stick), 3,000-100,000 (SSD drives)
- Each block wears independently, so a heavily written block can wear out long before a mostly-read block
  - *Wear leveling* is remapping of addresses to better balance the number of write cycles seen by each block
  - This is done transparently by the storage device, but can lead to unexpected performance drops

Adapted from Database System Concepts, 7th edition, Silberschatz, Korth and Sudarshan

# Indexing



# Indexing

- Indexing mechanisms used to speed up access to desired data.
  - E.g., author catalog in library
- **Search Key** - attribute to set of attributes used to look up records in a file.
- An **index** consists of records (called **index entries**) of the form

| search-key | pointer |
|---|---|

- The index is typically much smaller than the original data
  - E.g., 100X smaller
- How big does the pointer need to be?
  - Example: A pointer for 1GB of data
    - 1GB can be represented as an array with 30 bits (0's or 1's)
    - 000…00 points to the start of 1GB
    - 000…01 points to the first byte
  - General idea: take the size of the data, and figure out how many bits need to represent it
- Where would you store the index?
  - Usually in memory
  - → Index has to be small, since memory capacity is limited

# Index Evaluation Metrics

- Access types supported efficiently:
  - Records with a specified value in the attribute
  - Records with an attribute value falling in a specified range of values
- Access time
- Insertion time
- Update time
- Deletion time
- Space overhead

# Ordered Indices

- In an **ordered index,** index entries are stored sorted on the search key value.
- **Primary index:** in a sequentially ordered file, the index whose search key specifies the sequential order of the file.
  - The search key of a primary index is usually but not necessarily the primary key.
- **Secondary index**: an index whose search key specifies an order different from the sequential order of the file.

## Dense Index Files

- **Dense index** — Index record appears for every search-key value in the database.
- E.g. index on *ID* attribute of *instructor* relation

| | |
|---|---|
| 10101 | |
| 12121 | |
| 15151 | |
| 22222 | |
| 32343 | |
| 33456 | |
| 45565 | |
| 58583 | |
| 76543 | |
| 76766 | |
| 83821 | |
| 98345 | |

| | | | | |
|---|---|---|---|---|
| 10101 | Srinivasan | Comp. Sci. | 65000 | |
| 12121 | Wu | Finance | 90000 | |
| 15151 | Mozart | Music | 40000 | |
| 22222 | Einstein | Physics | 95000 | |
| 32343 | El Said | History | 60000 | |
| 33456 | Gold | Physics | 87000 | |
| 45565 | Katz | Comp. Sci. | 75000 | |
| 58583 | Califieri | History | 62000 | |
| 76543 | Singh | Finance | 80000 | |
| 76766 | Crick | Biology | 72000 | |
| 83821 | Brandt | Comp. Sci. | 92000 | |
| 98345 | Kim | Elec. Eng. | 80000 | |

# Dense Index Files (Cont.)

- Dense index on *dept_name*, with *instructor* file sorted on *dept_name*

| | |
|---|---|
| Biology | |
| Comp. Sci. | |
| Elec. Eng. | |
| Finance | |
| History | |
| Music | |
| Physics | |

| | | | | |
|---|---|---|---|---|
| 76766 | Crick | Biology | 72000 | |
| 10101 | Srinivasan | Comp. Sci. | 65000 | |
| 45565 | Katz | Comp. Sci. | 75000 | |
| 83821 | Brandt | Comp. Sci. | 92000 | |
| 98345 | Kim | Elec. Eng. | 80000 | |
| 12121 | Wu | Finance | 90000 | |
| 76543 | Singh | Finance | 80000 | |
| 32343 | El Said | History | 60000 | |
| 58583 | Califieri | History | 62000 | |
| 15151 | Mozart | Music | 40000 | |
| 22222 | Einstein | Physics | 95000 | |
| 33465 | Gold | Physics | 87000 | |

# Sparse Index Files

- **Sparse Index**: contains index records for only some search-key values.
  - Applicable when records are sequentially ordered on search-key
- To locate a record with search-key value *K* we:
  - Find index record with largest search-key value < *K*
  - Search file sequentially starting at the record to which the index record points

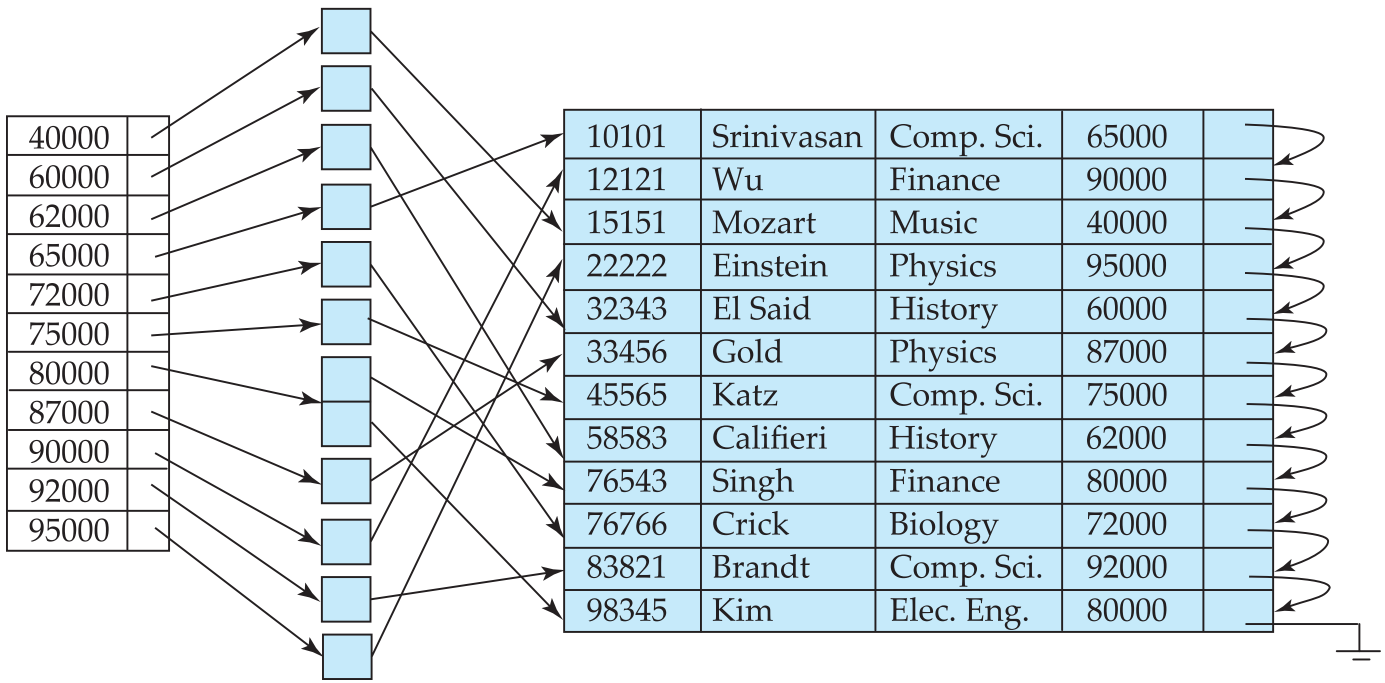
| | |
|---|---|
| 10101 | |
| 32343 | |
| 76766 | |

| | | | | |
|---|---|---|---|---|
| 10101 | Srinivasan | Comp. Sci. | 65000 | |
| 12121 | Wu | Finance | 90000 | |
| 15151 | Mozart | Music | 40000 | |
| 22222 | Einstein | Physics | 95000 | |
| 32343 | El Said | History | 60000 | |
| 33456 | Gold | Physics | 87000 | |
| 45565 | Katz | Comp. Sci. | 75000 | |
| 58583 | Califieri | History | 62000 | |
| 76543 | Singh | Finance | 80000 | |
| 76766 | Crick | Biology | 72000 | |
| 83821 | Brandt | Comp. Sci. | 92000 | |
| 98345 | Kim | Elec. Eng. | 80000 | |

- Compared to dense indices:
  - Less space and less maintenance overhead for insertions and deletions
  - Generally slower than dense index for locating records

# Secondary Index Example

- Secondary index on salary field of instructor

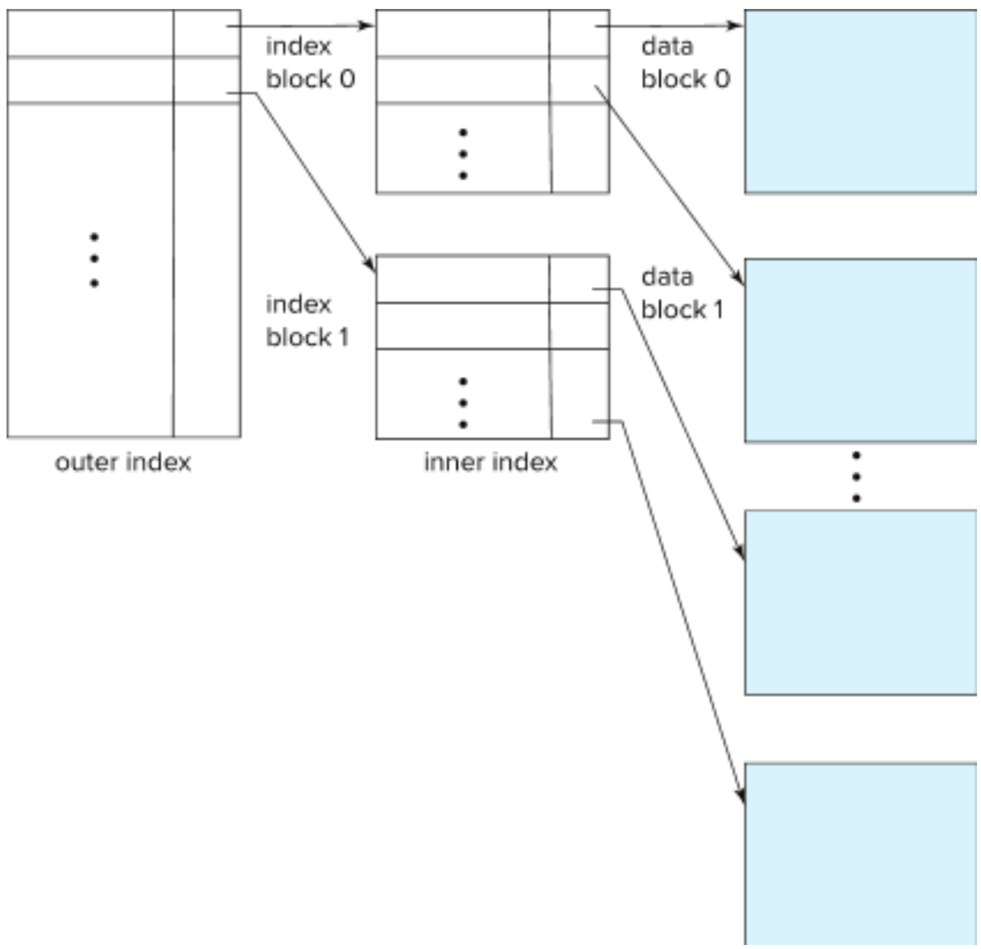



- Index record points to a bucket that contains pointers to all the actual records with that particular search-key value.
- Secondary indices have to be dense
  - Why?

# Multilevel Index

- If index does not fit in memory, access becomes expensive.
- Solution: treat index kept on disk as a sequential file and construct a sparse index on it.
  - outer index – a sparse index of the basic index
  - inner index – the basic index file
- If even outer index is too large to fit in main memory, yet another level of index can be created, and so on.
- Indices at all levels must be updated on insertion or deletion from the file.
- File systems often use a multilevel index (e.g., nested directories)

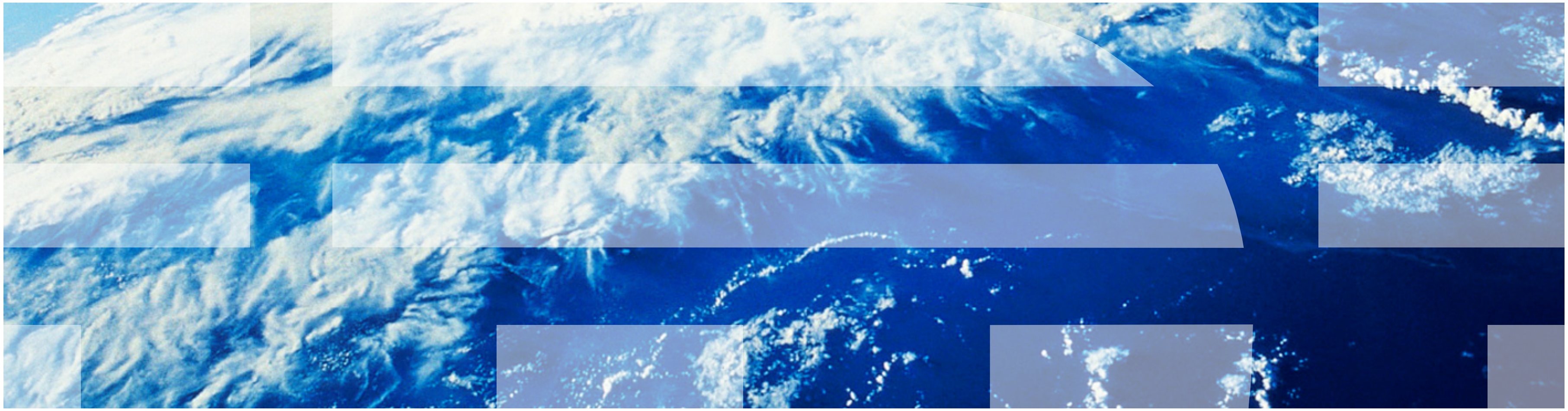
# Multilevel Index (Cont.)



# Index Update: Insertion

- **Single-level index insertion:**
  - Perform a lookup using the search-key value of the record to be inserted.
  - **Dense indices** – if the search-key value does not appear in the index, insert it
    - Indices are maintained as sequential files
    - Need to create space for new entry, overflow blocks may be required
  - **Sparse indices** – if index stores an entry for each block of the file, no change needs to be made to the index unless a new block is created.
    - If a new block is created, the first search-key value appearing in the new block is inserted into the index.
- **Multilevel insertion and deletion:** algorithms are simple extensions of the single-level algorithms

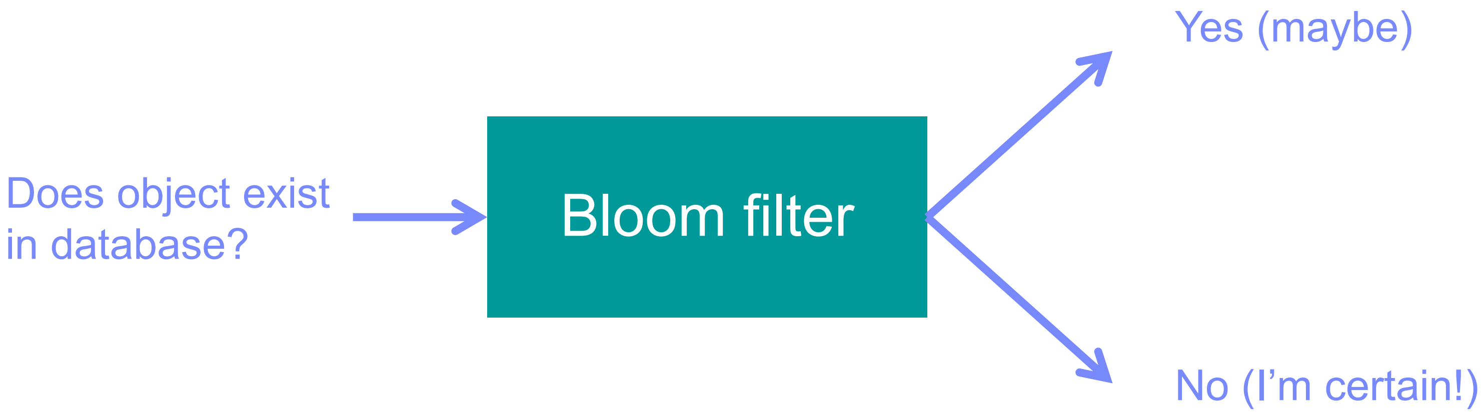
# Bloom Filter



# Motivation: Index doesn't fit in memory

- Example of a typical database:
  - 64GB memory
  - 2TB flash disk
  - Average key+value (e.g., entry) size: 50B → database needs to store 40 billion keys!
- A pointer needs to locate a key among 40 billion keys
  - Minimum pointer size: 36 bits ~ 4.5 bytes (let's round it to 5 bytes)
  - Index size = number of keys * byte rounded pointer size ~ 200GB
  - Does not fit in memory
- Therefore, we must use a multi-level index
  - Outer index in memory
  - Inner index on disk
- Minimum time reading a single object: 1 memory access + 2 flash accesses ~ 200us
- **What if object doesn't exist in the database?**
  - Still 200us!
- Can we do better?

# Bloom filters [Bloom 1970]: Approximate way to determine if object exists



# Bloom filter parameters

- An array of m bits (can only be ‘0’ or ‘1’)
  - Array initialized to 0
- k independent **hash functions** $h_1, h_2, \dots h_k$ that return a number between $1, \dots m$

# What is a hash function?

- What is a hash function?
  - $h(x) = y$, where y is a uniformly random number
  - In our case, y is a random number between $1, .. m$

- If $h(x_1) = h(x_2)$, there is some probability that $x_1 = x_2$
- If $h(x_1)! = h(x_2)$, we are sure that $x_1! = x_2$

# Algorithms: check membership and add membership

- To check if x is a member of the bloom filter, check whether $h_1(x), \dots h_k(x)$ are all set to 1
  - If not, x is definitely not a member
  - If yes, x might be a member
    - There can be false positives!

- To add x, set the positions of $h_1(x), \dots h_k(x)$ all to 1
  - Some positions might already have been set as 1

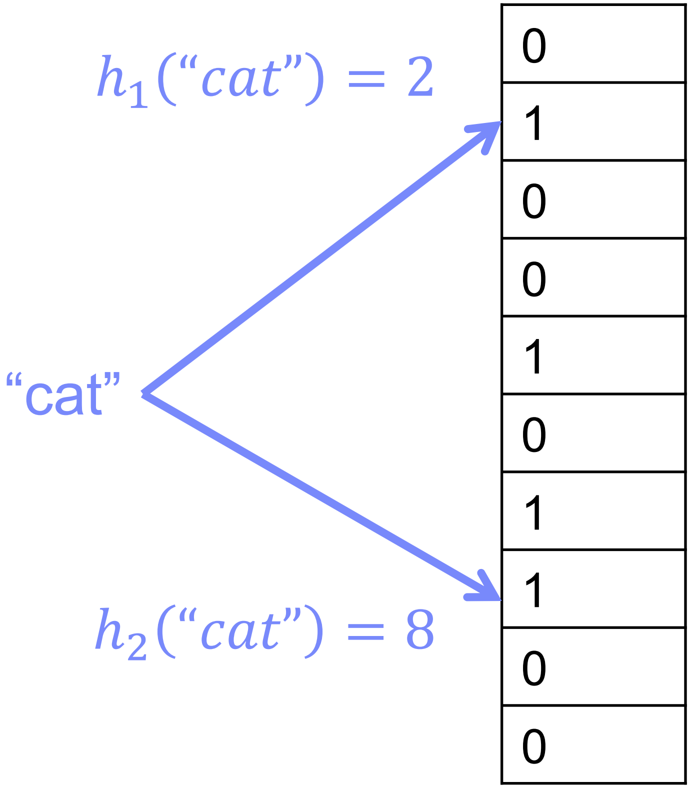
# How does a bloom filter work? Example

m = 10
k = 2

| |
|---|
| 0 |
| 1 |
| 0 |
| 0 |
| 1 |
| 0 |
| 1 |
| 1 |
| 0 |
| 0 |

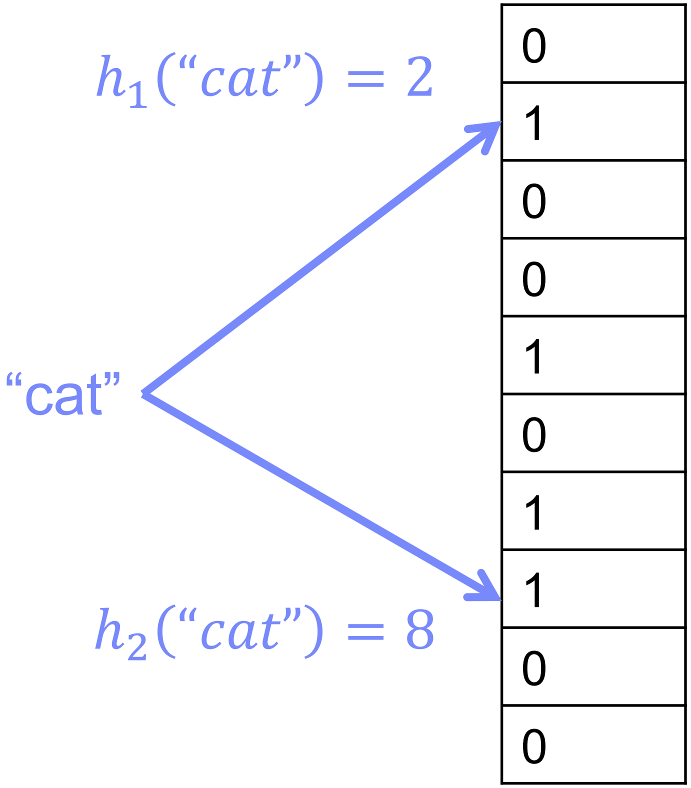
# Is cat in DB?

m = 10
k = 2



# Is cat in DB? Maybe!

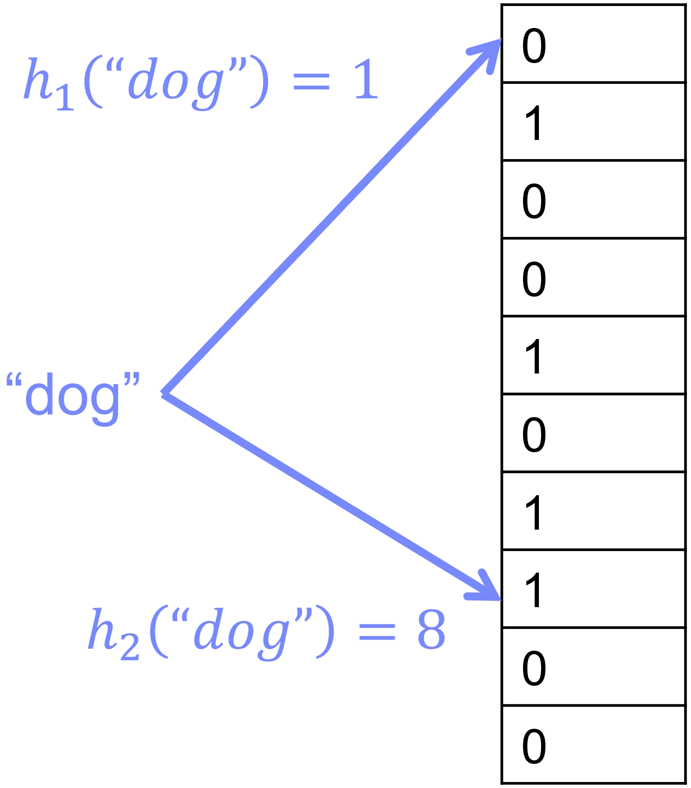
m = 10
k = 2




Cat might exists in DB!

# Is dog in DB?

m = 10
k = 2

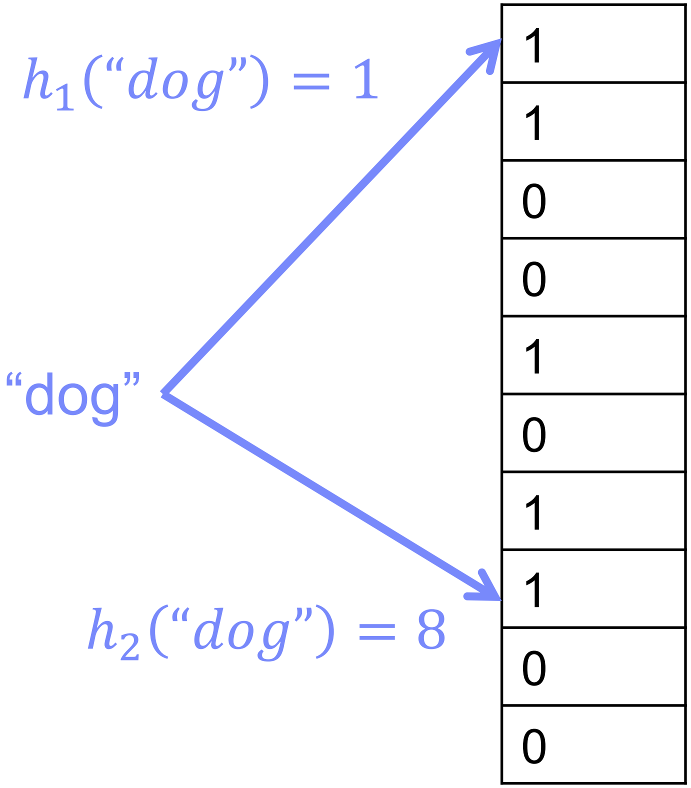



Dog definitely does not exist in DB

→ We don’t need to read from disk

# Add dog to DB

m = 10
k = 2

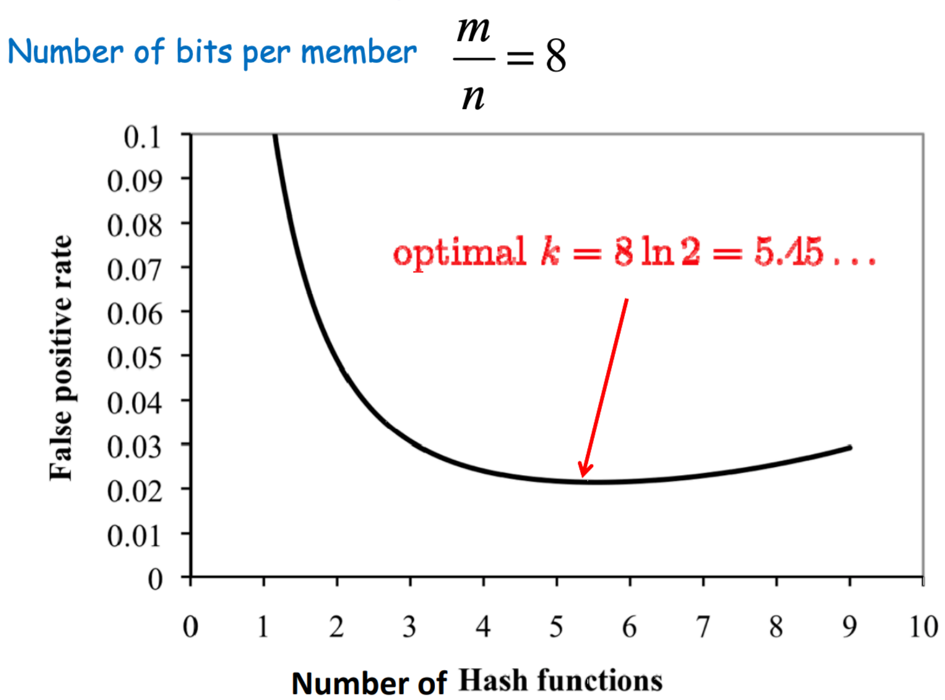


# Goal: low false positives

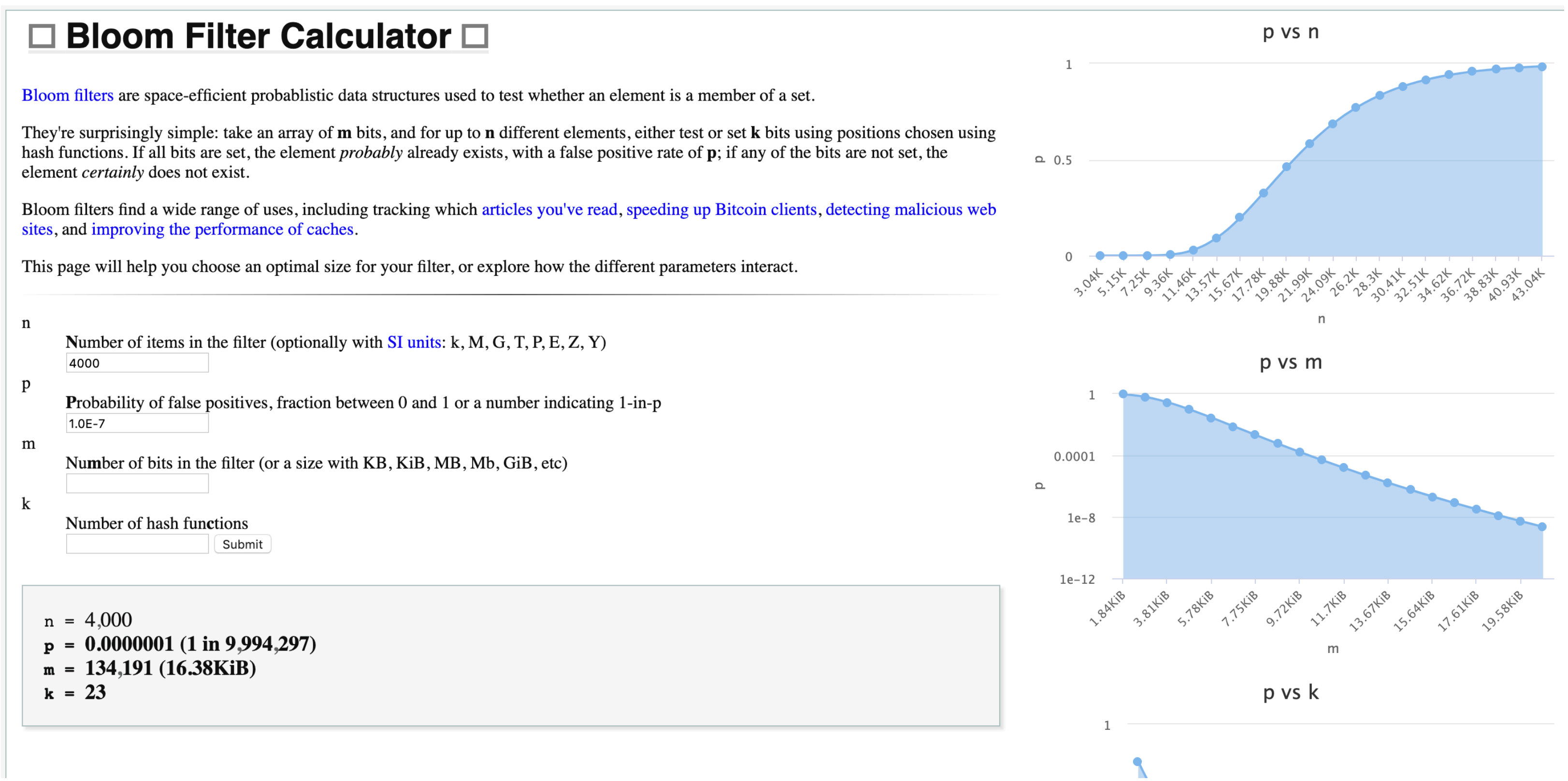
- Define n as the total number of unique objects that might ever be inserted into the database
  - For example, for a bank database that uses account ID as keys, this is the total number of accounts the bank will ever have
- Let's assume $kn < m$

# False positive probability (credit: Simon S. Lam)

- The size of k is a trade-off:
  - A higher k increase the number of hash functions that might map to 0
  - But also ”depletes” the available 0 slots in the bloom filter
- Optimal k: $k = \frac{m}{n} ln2$



# Bloom filter calculator (https://hur.st/bloomfilter/)

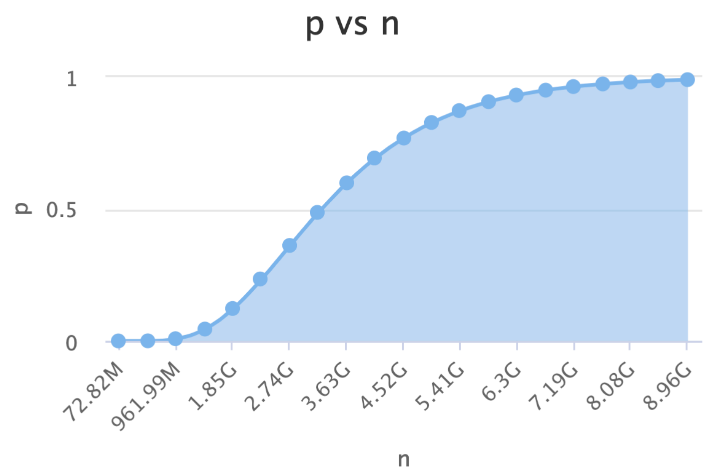


## Trade off memory space vs. speed

- Larger bloom filter:
  - Reduces false positives → fewer reads to disk → lower latency, higher throughput
- But…
  - Takes up more space in memory → less space for caching database index entries in memory → higher chance of going to disk → higher latency, lower throughput

# Example of space vs. speed trade off

- Example: database has 2GB of memory for caching and 100GB of flash
  - Needs to store 1 billion entries (each ~100B)
- Flash access is 100us, memory access is 100ns
- Which bloom filter parameters would you choose?
  1. 600MB bloom filter:
     - Bloom filter false positive rate of 9%
     - 1.4GB of DRAM left → index cache hit rate of 90%
  2. 1.1GB bloom filter:
     - Bloom filter false positive rate of 1%
     - 0.9GB of DRAM left → index cache hit rate of 70%

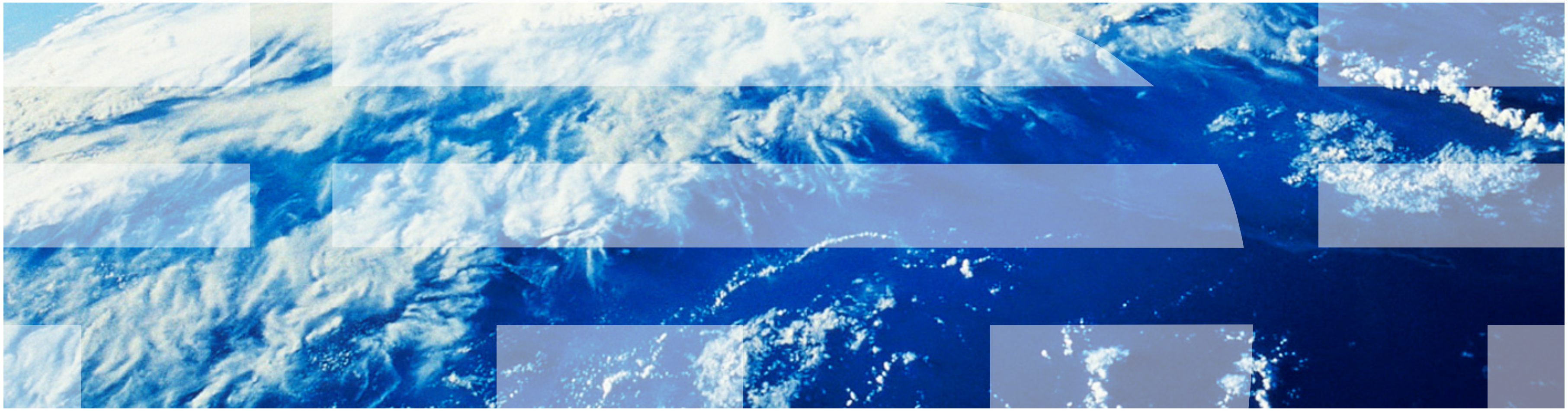



- 60% of requests return object does not exist:
- $\boldsymbol{avg\ latency} = \mathbb{P}(exists) \cdot (\mathbb{P}(cached) \cdot 100ns + \mathbb{P}(not\_cached) \cdot 100\mu s) + \mathbb{P}(doesn't\_exist) \cdot (\mathbb{P}(true\ positive) \cdot 100ns + \mathbb{P}(false\ positive) \cdot 100\mu s)$
- Scenario 1
  - 0.4 * (0.9 * 100ns + 0.1 * 100us) + 0.6 * (0.91 * 100ns + 0.09 * 100us) = **9.49us**
- Scenario 2:
  - **12.64us**

## Other issues with bloom filters

- Can get “depleted” over time
- Need to estimate number of unique entries in advance
- Do not support deletes!
  - Why?
- Improvements: counting bloom filters, cuckoo filters, learned bloom filters, elastic bloom filters… This is a hot research area!

# Lecture 7



# Recap of lecture 6

- **Flash storage**
  - No moving parts, faster than magnetic disk
    - No seek/rotation/transfer latencies
  - Reads perform differently than writes
    - Reads can be read at a block granularity (e.g., 4KB)
    - Writes need to be much larger for good throughput
    - Erase granularity != write granularity
    - Modern flash devices write over multiple channels
- **Indexing**
  - Dense index (each key has an entry in the index)
  - Sparse index (each key **range** has an entry in the index)
    - Requires keys to be sorted
  - Multilevel index (outer index sparse)
  - Issues with insertions/deletions

# Recap of lecture 6 (continued)

- **Bloom filters**
  - Does key exist in database?
  - Possible answers: no/maybe
    - If it says no, we know for sure key is not in database
    - If it says maybe, we need to read database to check
  - Uses k hash functions to check if key is in DB
    - If all point to an entry of “1”, return maybe
    - If not, return no
  - We want to minimize false positive rate of “maybes”
    - The larger the bloom filter, the lower the false positive rate, but the more space it takes up in memory
  - Trade off between bloom filter size and cache size
    - We will talk more about caches hopefully in a few of weeks

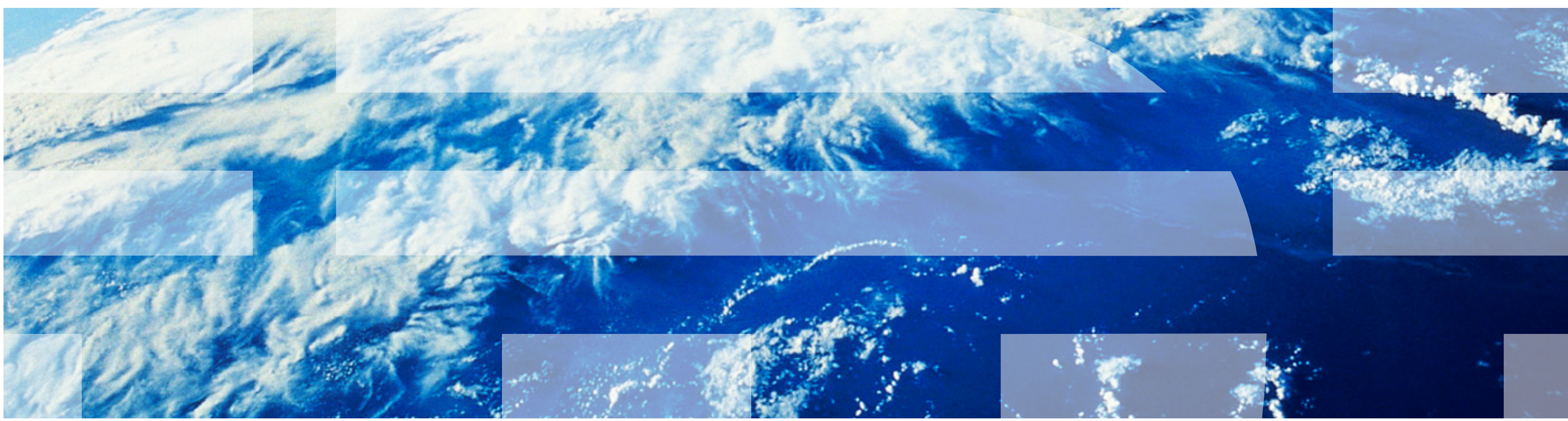
# Today: Wrap up single DB, start looking at distributed systems

- Key-value stores
  - Spotlight on RocksDB
- Databases on top of key-value store
  - Spotlight on MyRocks
- Partitioning
- Replication
- Distributed file systems
- If we have time:
  - Distributed transactions and 2 phase commit

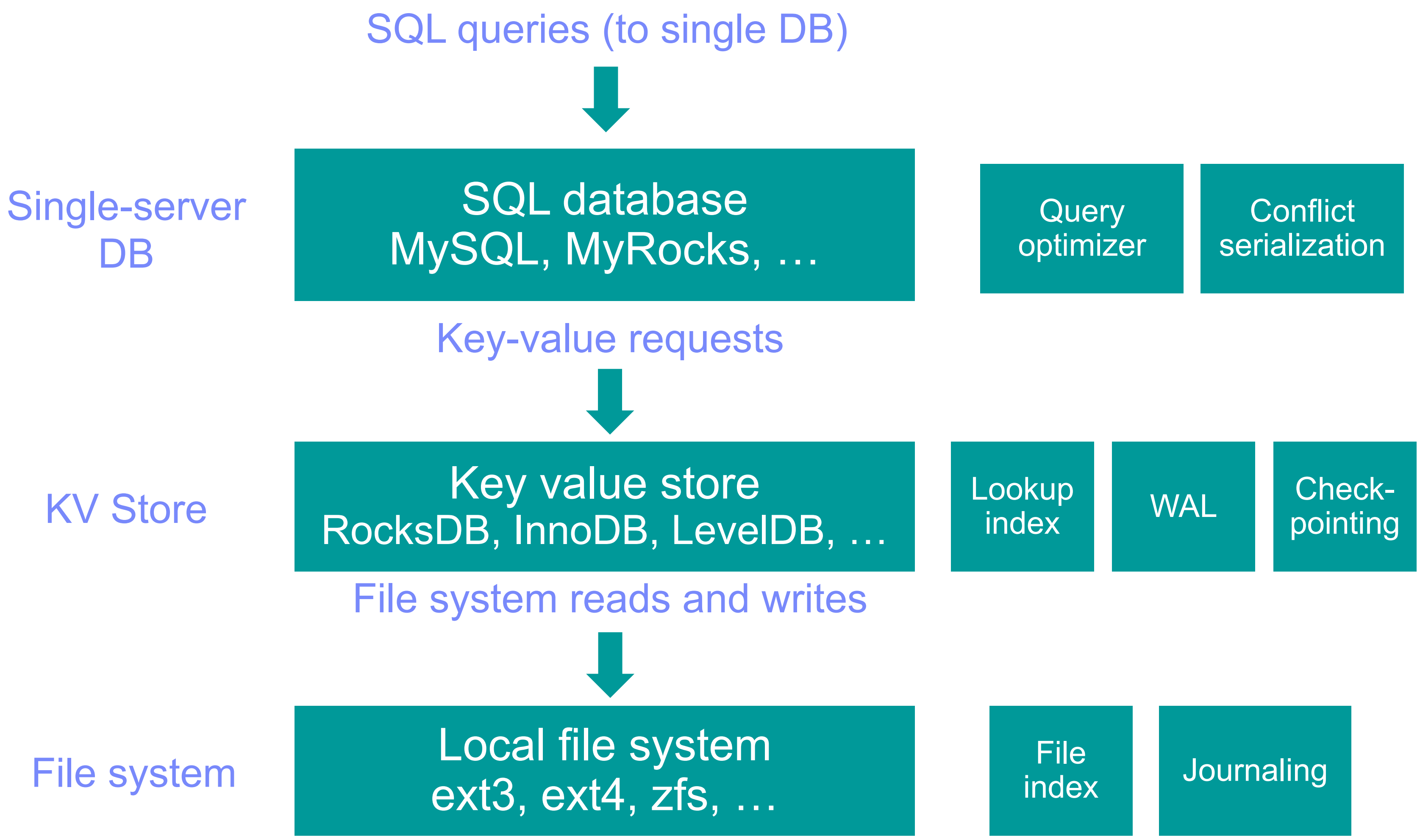
# Logistics

- Class is now pass/fail
- Midterm
  - You can take it anytime you like, starting Tuesday noon this week (03/31), ending Tuesday noon next week (04/07)
  - 2 hours and 15 minutes
  - Fully on Canvas (in the quiz section)
  - Open slides
  - Don't cheat – the class is pass/fail, so this is for your own learning/assessment
  - I recommend taking it during TA office hours
- Homework 2 (Spark) will be released next week
  - Done in pairs
  - We will make the last questions optional
- TBD the format/dates of homework 3 and final
- Final is likely to be similar format to midterm (we'll see how it goes)
- You will get graded on all assignments, but final grade will be pass/fail
  - Criteria is not determined yet – but in general we will be flexible, especially for students with extenuating circumstances

# Database Architecture

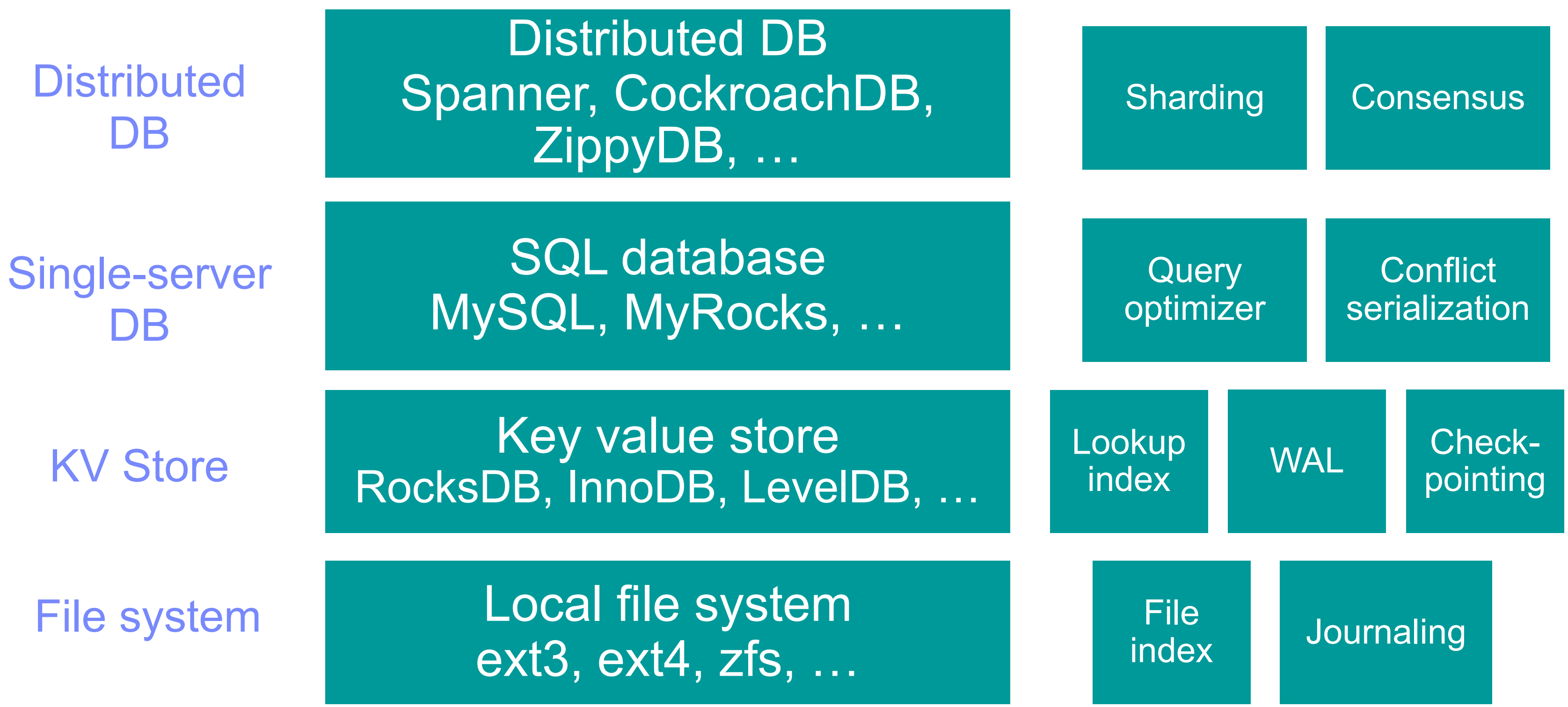


# Modern databases often consist of several layers

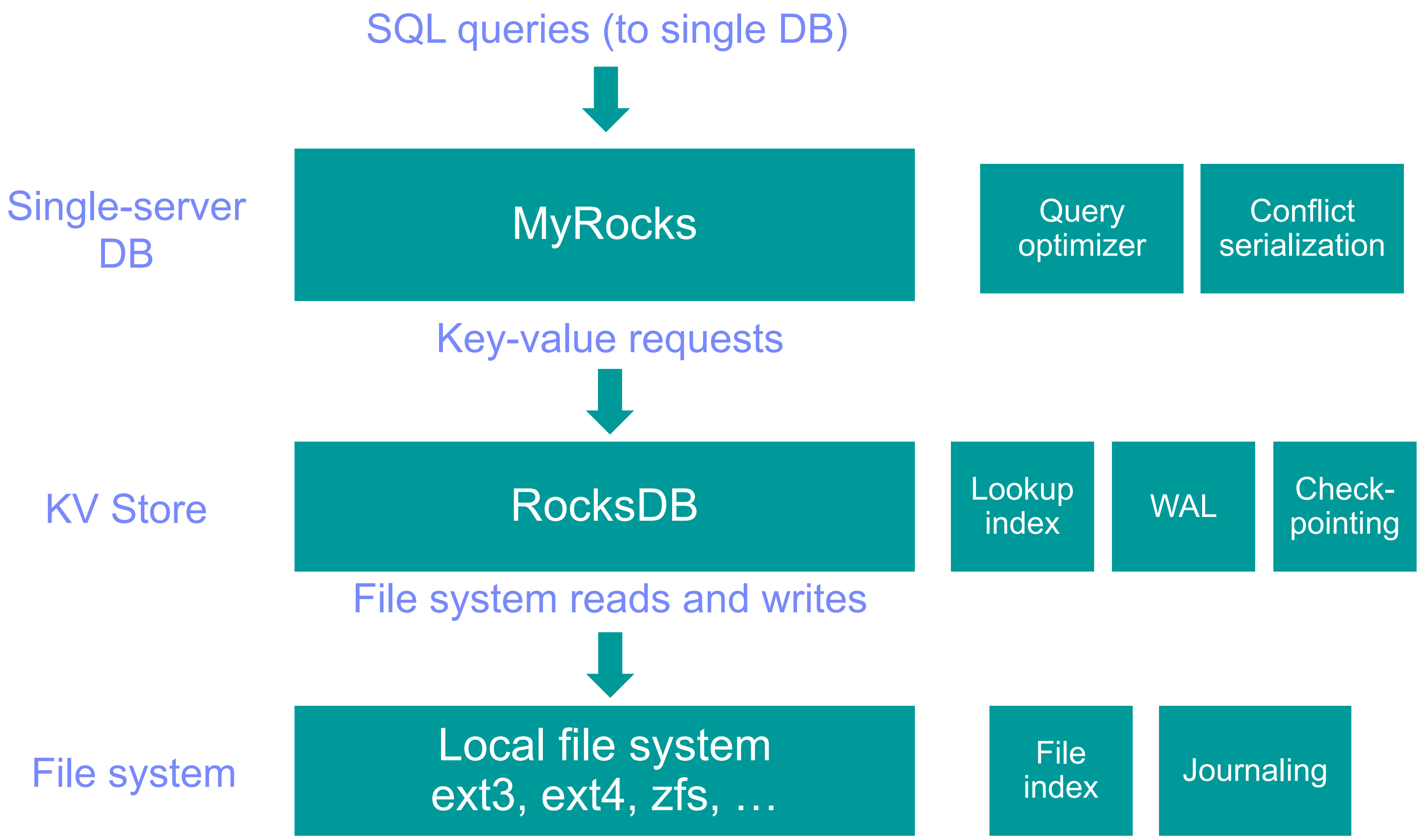


# Distributed databases add even another layer

We'll talk more about distributed computer systems later…



# We'll focus on one example database: MyRocks + RocksDB



# Very brief overview of local file systems

- This is the file system running on the server itself
  - Similar to the file system on your computer!
- Maps physical storage into files, which can be read/written by applications
- Caches some data in memory (file system cached is called *page cache*)
- Logging (similar to WAL) called *file system journal*

- Databases (and other big data systems) often disable many features of file system
  - Don’t care about directories
  - Don’t rely on file system journal for maintaining ACID
  - Often want to manage their own cache

## Key-value Stores

- Databases with a really simple interface
  - Do not support SQL
- Get (key)
- Put (key, value)
- Delete (key)
- Sometimes:
  - Update (key, value)
  - Multiget (key1, key2, key3, …)
  - Get_range ([key_i, … key_j])

- Key-value (KV) stores can be used on their own (NoSQL) or can be a foundation for an ACID SQL database

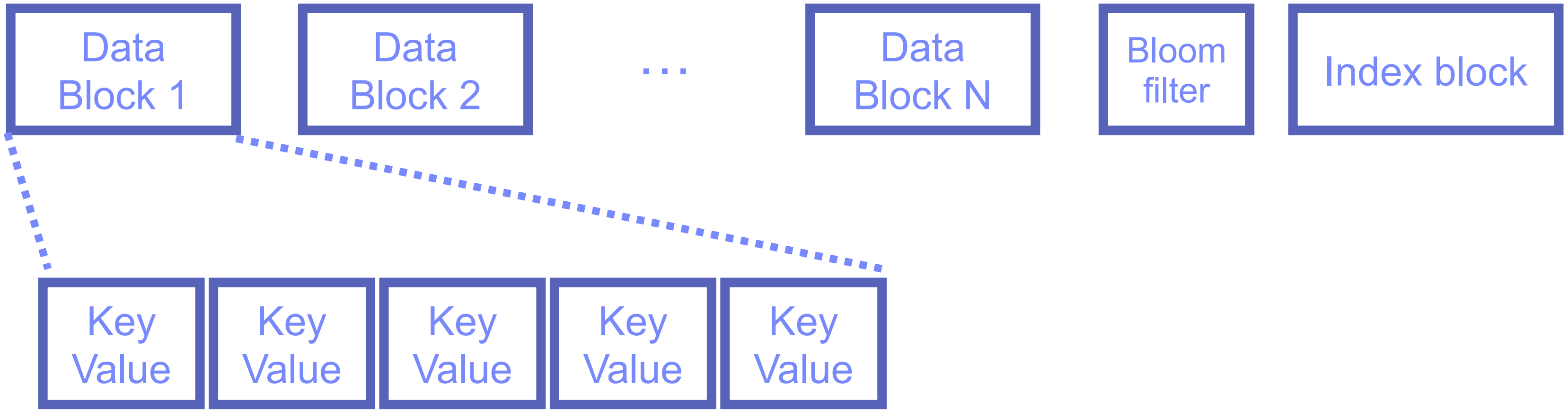
# Showcase: RocksDB

- Open source KV store built by Facebook
  - Based on another open source KV store, LevelDB, built by Google
- Optimized for flash
  - Large contiguous writes
  - Generates a relatively small number of writes
- Optimized for range queries
  - Applications often need contiguous range of keys (e.g., get an entire column from a database)

# RocksDB components

- Memtable
  - In-memory data structure
  - Stores all incoming writes
    - Why is this a good idea?
  - All writes go to Memtable
  - Small: 64/128MB
- Logfile
  - Write ahead log
  - Sequentially written to
  - Stored persistent in storage (not memory)
- SSTfile (Static Sorted Table File)
  - Data structure that stores the contents of the database in storage
  - A file that contains a set of **sorted** key-value pairs (keys + values)
  - Organized in **levels**
  - Immutable (i.e., write-only, can never be updated)
    - Why is this a good idea?
  - Sorted data → makes it easier to lookup keys

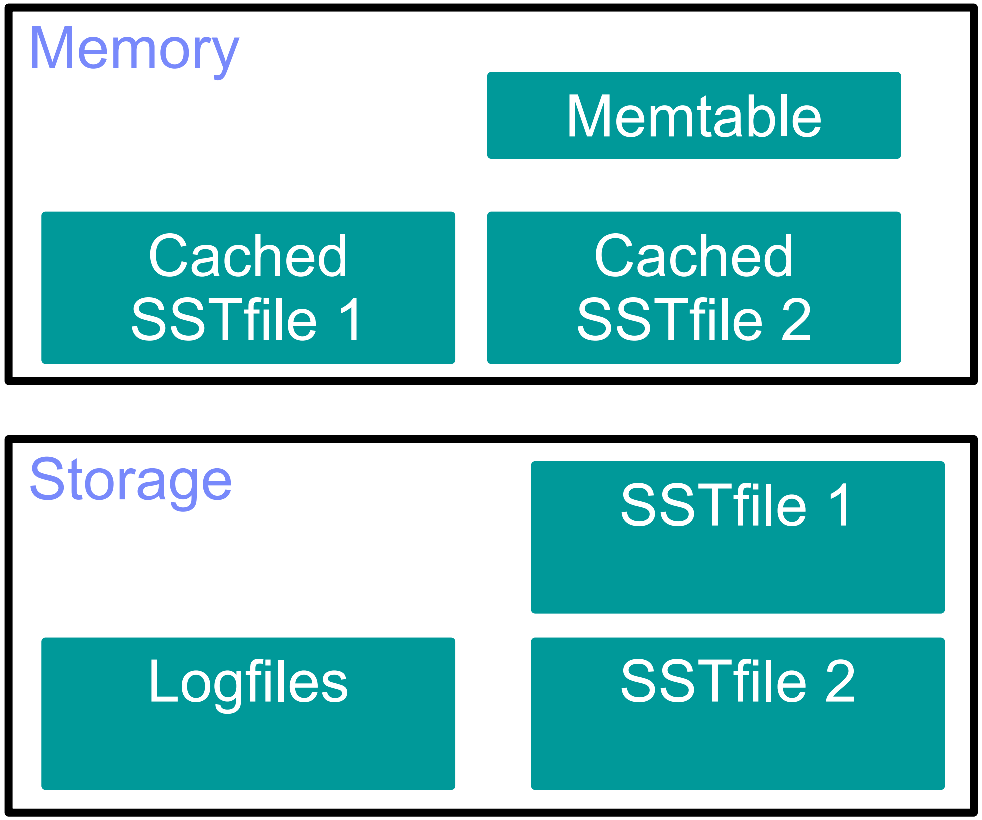
# SSTfile structure



# SSTfiles and Memtables

- On-disk SSTfiles are always loaded into memory before they are read
- All **writes** go directly to Memtable
- **Reads** check the Memtable first, then the SSTfiles indices
- SSTfile indices and bloom filter are usually cached permanently in DRAM (if they fit)
- Periodically Memtable is **flushed** to disk
- Periodically old on-disk SSTfiles are **merged/compacted** to create new SSTfiles
  - Recall, SSTfiles are immutable, so we need a way to remove stale data (updated/deleted values)
  - Stored in a data structure called **Log-structure Merge Tree (LSM-Tree)**

# Simplified architecture



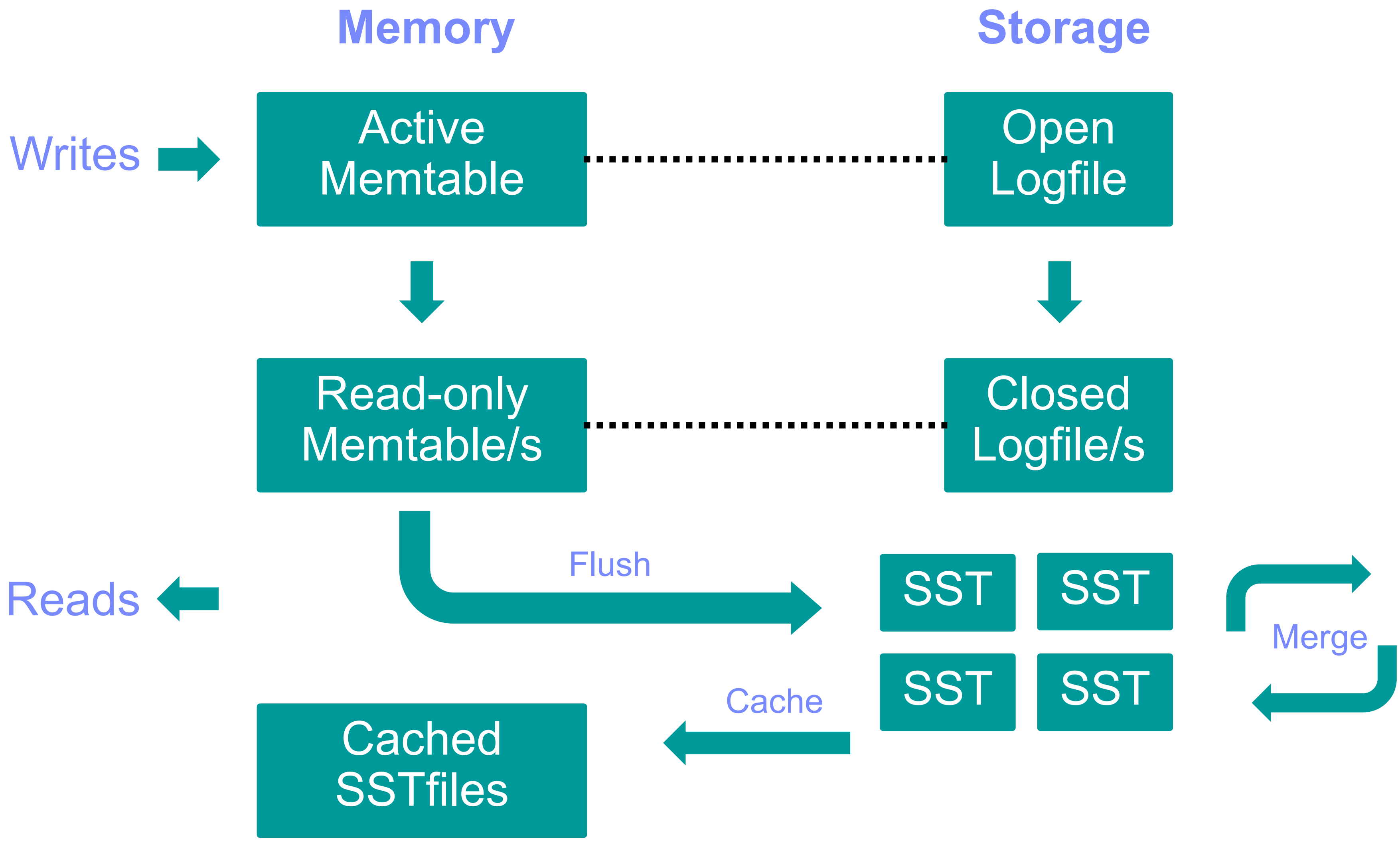

## SSTfile index

| | |
|---|---|
| Key | Offset |
| Key | Offset |
| … | … |

## Simplified SSTfile data

| | | | | |
|---|---|---|---|---|
| Key | Value | Key | Value | … |

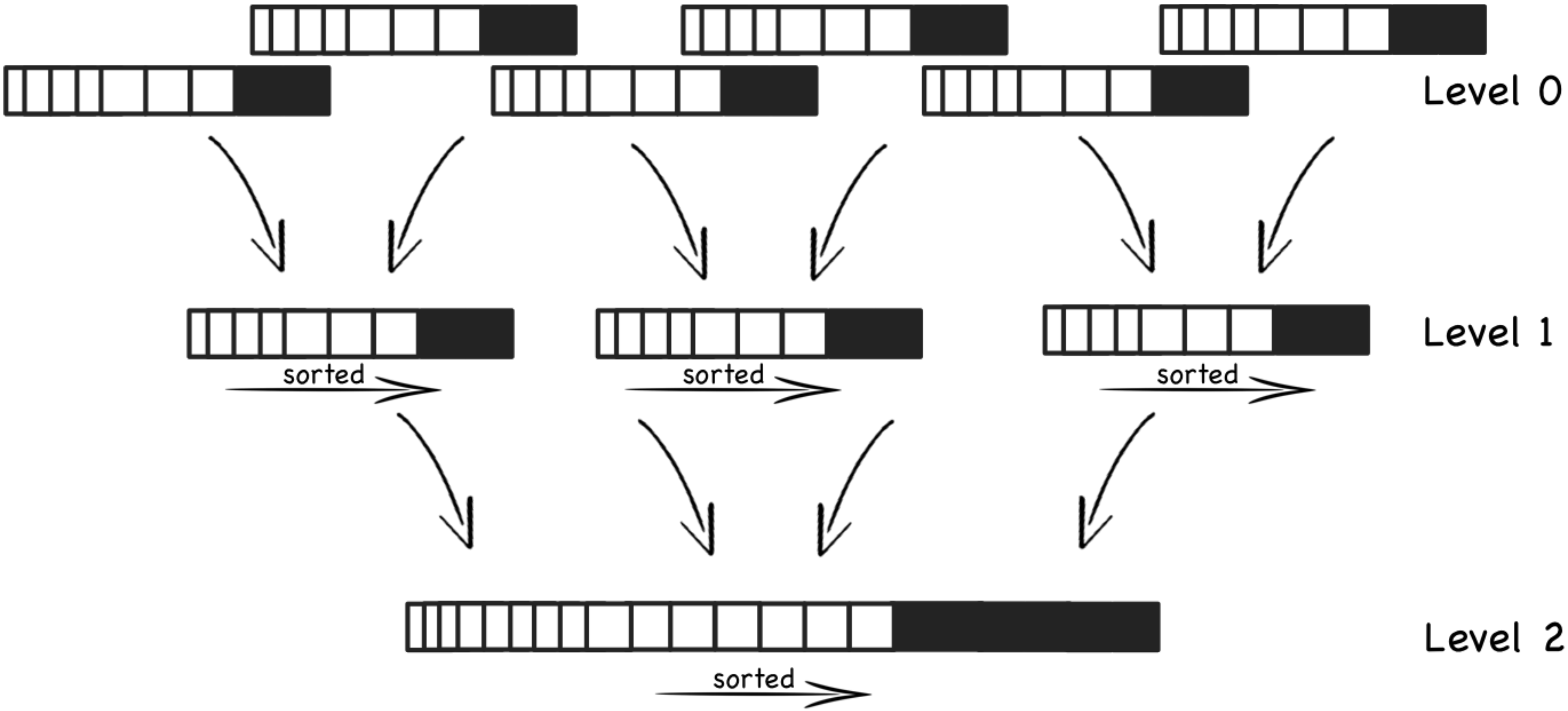
## Basic functions



# How does RocksDB maximize performance

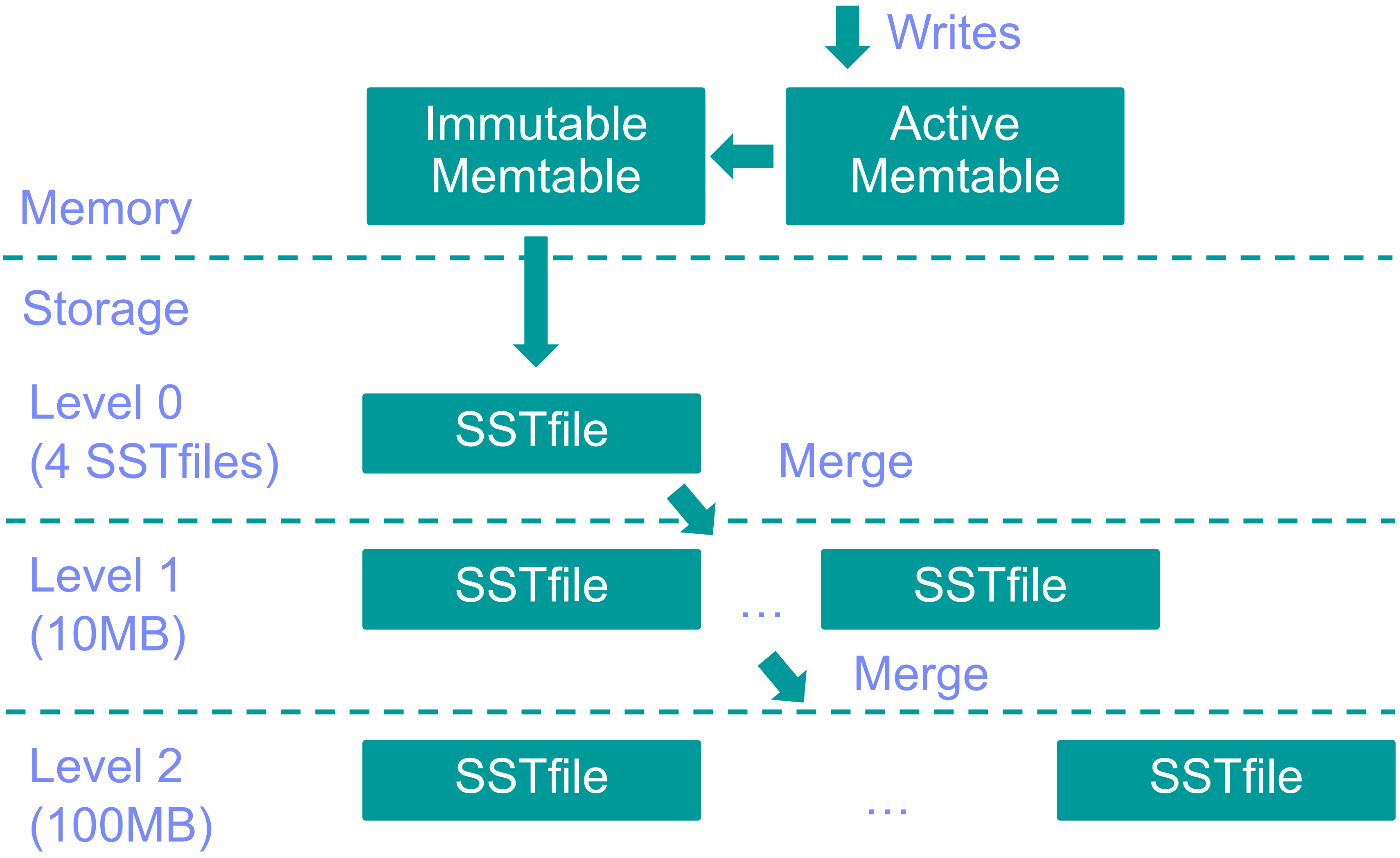
- Data write (insert/update)
  - New data written to memory (Memtable) and to logfile sequentially
  - Memtable fills up → flushed to SSTfile on disk
- Data read
  - Memtable in memory
  - SSTfile indices in memory
    - Use bloom filters to determine existence

# Log-structured Merge Tree (LSM-Tree)




Compaction continues creating fewer, larger and larger files

# RocksDB LSM-Tree Architecture



# LSM-Trees

- Most recently written data is at the top of the tree
  - Newer versions are in a higher level than older version
    - Why? Because older versions get compacted
  - LSM-Tree is searched in order from the highest level
- In RocksDB, highest level is in memory
  - Not sorted
  - Memory has good random write performance (not the case for flash/magnetic disk)
- Data that ends up in the lower levels is not updated frequently

# Merging

- Background process periodically merges SSTfiles
  - Parallel computations on different parts of the DB occur simultaneously (using locks)
- Merges SSTfiles from higher level to larger SSTfile in lower level
  - Removes old versions of the same key
  - Removes deleted or overwritten keys
- Each level is 10 times larger than the previous
- In level 0 different SSTfile might contain overlapping key ranges
- In levels 1-n SSTfile key range are not overlapping
  - For example:
    - SSTfile 1: key range: [0, 5]
    - SSTfile 2: key range [6, 202]
    - SSTfile 3: key range [205, 421]
- Every level is 10 times larger than the other
  - Most data sits at the bottom level

# Concurrency

- Database maintains a lock table
- Every update acquires a lock beforehand
- Actively check for conflicts

# MyRocks (SQL and ACID over RocksDB)

- Much of the logic sits in RocksDB
- Implements ACID on top of RocksDB
  – Uses RocksDB locks to implement isolation
- Implements SQL over RocksDB API
  – Translates rows/columns to gets/puts/multigets